Self-Supervised Dense Object Descriptors with Class Awareness

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Abstract: In this paper we address the problem of inferring self-supervised dense semantic correspondences between objects in multi-object scenes. The method introduces learning of class-aware dense object descriptors by providing either unsupervised discrete labels or confidence in object similarities. We quantitatively and qualitatively show that the introduced method outperforms previous techniques with more robust pixel-to-pixel matches. We also show an example robotic application - grasping of objects in clutter based on corresponding points.

Keywords: Self-Supervision, Descriptor Learning, Object Correspondence

1 Introduction

Self-supervised methods allow models to train with no manual labelling, thus improving the ability to scale and learn from more data. In robotic applications, they could potentially allow a robot to learn continuously 'in the wild'. Robots of the future would benefit from the ability to learn how to interact with many objects, including unseen novel ones. One particular problem is finding accurate pixel correspondences between similar objects in such a way that a robot agent recognises the corresponding parts between two items and manipulates them in similar ways.

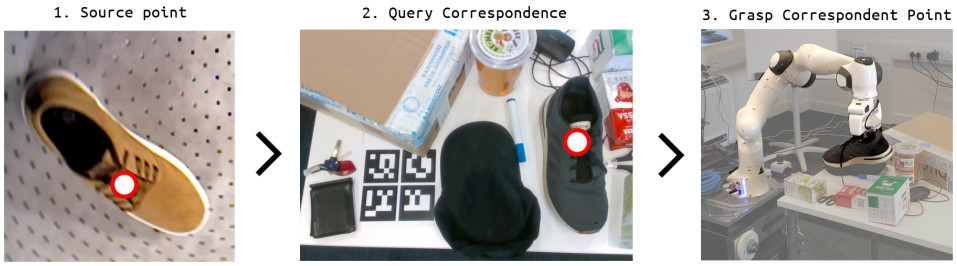

Figure 1: Correspondence (red circle) produced by our *DON+Soft* method used for robot grasping.

A recent work producing self-supervised object descriptors, namely Dense Object Nets [1] (DONs), has been applied as a representation learner for visuomotor policies [2, 3] improving onto previous end-to-end methods [4]. While DONs produce excellent point correspondences between similar objects, without access to ground truth classes they fail to find robust matches in multi-object scenes and produce false positives. In this work, we propose a method for class-aware Dense Object Network that adds unsupervised classification to the DON, and show that it leads to more informative descriptors that are better suited for correspondence generation in multi-object scenes. We present two variants exploring different ways of representing the object classes: "hard" discrete labels and "soft" labels, reflecting our confidence in the similarity between the objects. We demonstrate that our method is better than the state-of-the-art in finding correspondences in multi-object images, while simultaneously improving performance of on single-object images. A real example application is shown using a mobile manipulator. This method could enable future work on more complex tasks such as unsupervised learning of category-level affordances and manipulation of objects in clutter.

Submitted to the 5th Conference on Robot Learning (CoRL 2021). Do not distribute.

Paper Organisation: We present related work in Sec. 2, followed by a more detailed overview of Dense Object Nets (Sec. 3). We then present our method in Sec. 4. Qualitative and quantitative evaluation is presented in Sec. 5. A discussion of the method's limitations and failures as well as possible applications is shown in Sec. 6.

2 Related Work

In this section we briefly overview recent advances in descriptor learning. We then review methods for unsupervised classification and class disentanglement.

Our work focuses on self-supervised learning of descriptor representations, such that the descriptors of similar points belonging to similar object are consistent across time, view, and object instance. Our method builds upon Dense Object Nets (DONs) [1] which makes use of 2D pixel to 3D point projections as a supervisory signal. The method is described in more detail in Sec. 3. Most other works on descriptor learning such as [5, 6, 7] make use of fully- or weakly-supervised learning requiring large amounts of human-annotated data and do not make efficient use of depth data, which robots usually have access to. Several methods relieve the need for annotations by using 3D CAD models of the observed objects [8, 9], however this is not applicable when encountering novel objects. Many works make use of spatio-temporal consistency across video frames, using tracking trajectories or multiple modalities: [10] learns unique descriptors via optical flow contrasive learning showing the dense descriptors trained on dynamic data. A related method is the semi-supervised S3K [11], which uses multi-view consistency to produce keypoints with high accuracy. With only few ground truth examples, the method is able to learn 3D keypoints by estimating the projections of 2D keypoints. It proves to be useful for applications such as cable plug-in, where keypoints do not have to be bound to a physical location on the object, as long as they are consistent across views. However, it does not produce correspondences. We are not aware of any work that produces pixel-pixel correspondences in multi-object scenes, based on unsupervised or self-supervised training without ground truth models, which is introduced in this paper.

For our method to work, we require a way of assessing the similarity or dissimilarity between objects and disentangling their representations. This can be done by assigning some discrete class labels to each object or measuring our confidence in the similarity of object pairs. Most recent works use unsupervised clustering techniques such as mean-shift and K-Means in combination with embeddings [12, 13, 14]. Patten et al. [15] improve on previous approaches by considering geometric similarity and experience queries. Recently, Tan et al. [16] showed that clustering of object embeddings alone is not enough. Instead, they propose a method for similarity measurement and triplet sampling via random walker graphs. Their method demonstrates state-of-the-art results on various benchmarks. We use it as an inspiration to our method and provide further details in Sec. 4.3.2.

3 Dense Object Nets

Dense Object Nets [1] are the foundation of our method. In this section we explain how they work and identify their current limitations. DONs learn a dense descriptor representation of RGB inputs that is applicable to both rigid and non-rigid objects. It uses the strong prior of depth information taken from an RGB-D camera, and knowledge of a robot manipulator's pose to project 2D image pixels onto a reconstructed 3D model, thus learning correspondences between different views of the same 3D points. In particular, this is done by having a robot point a camera towards an object and move around to capture it from different views. In Siamese fashion, the model is fed pairs of augmented images from which pixels are randomly sampled. Pixels corresponding to the same 3D point are considered 'matches' while any other random pair of pixels are considered 'non-matches'. The loss is the sum of match and non-match losses defined as follows:

$$L_{match} = \frac{1}{N_+} \sum_{N_+} ||d_a - d_b||_2^2 \tag{1}$$

$$L_{non-match} = \frac{1}{N_-} \sum_{N_-} \max(0, M - ||d_a - d_b||_2)^2 \tag{2}$$

where d_a and d_b are the output descriptors at the given pixel pair and N_+ is the total number of match pairs. Similarly, N_- is the total number of non-matches. M is a margin hyperparameter determining

the minimum distance between non-match pairs - if a non-match pair is closer than M, the loss is increased. While L_{match} encourages true pairs to be similar, $L_{non-match}$ ensures the pixels don't all converge to the same descriptor. Since the robot has no knowledge of the object's class, the learned descriptors tend to share the same descriptor space for all objects. While the original work shows that when the ground truth class is known, the descriptor subsets can be distinctly separated, it does not propose how to implement this and remove the use of ground truth.

4 Method

The method presented in this section tries to solve the problem of disentangling the descriptor spaces shared by DON descriptors by including class awareness.

4.1 Problem Setup

The inputs used for training are a set of n sequences $S = \{S_1, S_2, ..., S_n\}$, where each sequence contains timed data for a single object $S_i = \{O_1^{(i)}, O_2^{(i)}, ..., O_t^{(i)}\}$. The data $O_t^{(i)}$ for each timepoint t and object (i), consists of a camera pose, full RGB and Depth image and their respective object-masked RGB and Depth images, whereas a 3D TSDF reconstruction is also generated for the whole sequence. In this paper, each *training* sequence strictly contains a single instance of a single object, while during *inference* we can work with both single and multi-object sequences. We discuss how the method could be adapted to train from multi-object sequences in Sec. 6. We refer to each distinct object as an **instance class** and its grouping as a **category**, e.g. different hats would belong to different instances but the same category. Given S we want to learn visual descriptors that are robust over different objects.

4.2 Training Data

Figure 2: Samples of RGB object images used as training data, real (left) and simulated (right).

For our training we use (i) real-world data from [1] and (ii) simulated data produced by us (see Fig. 2). The real world data consist of deformable objects such as shoes and hats. For the simulated data we placed a Gazebo-simulated Franka Emika Panda equipped with a RealSense RS200 RGB-D camera, placed 3D objects taken from the 3D GEM dataset [17] in randomised poses. We used 3D models of drinking cans and books that have the same or similar shapes but different textures. In total, we used 30 simulated scenes, 63 real scenes, and over 50,000 images. Samples of the datasets are shown in Fig. 2. Note, that because of the use of background augmentation in DON, the unrealistic scene in the simulated images does not affect the training.

4.3 Class-Aware Dense Object Nets

To disentangle the descriptor subsets used by different objects, most straightforward is to find non-match pairs between them and learn to repel them. We considered two method variants: (i) *DON+Hard* producing discrete "hard" labels by assigning each object instance to a cluster or (ii) *DON+Soft* using similarity-based triplet sampling and continuous "soft" confidence scores between object sequences. Both variants use the same DON model for dense correspondence, and similarity graph for object disentanglement, differing mainly in data flow, sampling and loss generation, as described below (see Fig. 3).

4.3.1 Dense Object Net

For DONs we use a 34 layer, 8-stride ResNet architecture. Its output descriptor image is upsampled to the original input size and has shape (H, W, D_{desc}), where H and W are the input image height and width, and D_{desc} is the number of descriptor dimensions.

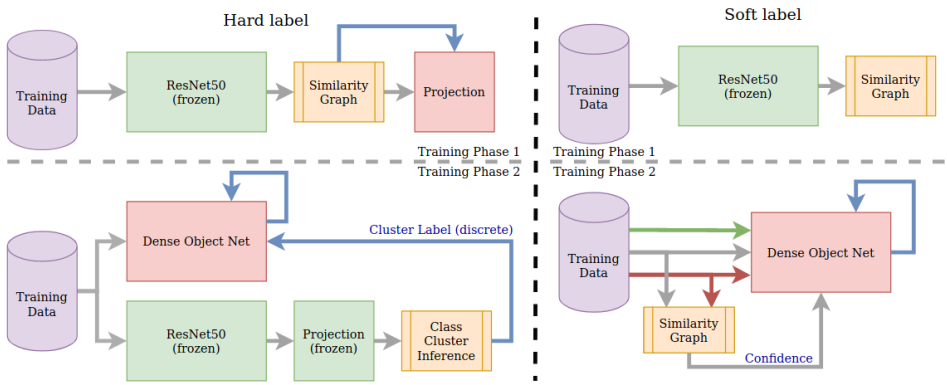

Figure 3: The simplified data flow for the hard (left) and soft (right) label variants of our method. Blue arrows signify self-supervisory signals, grey - the main data flow, green and red arrows denote positive and negative triplet pairings in the soft labels variant.

4.3.2 Similarity Graph

The method we use for object disentanglement is based on a recent work [16] which consists of a similarity graph and random walker sampling. Object view variance is addressed by using clustering techniques, while a graph representation is used to guide the classifications to more probable pairs. With each sequence representing a node, an undirected graph is created. The edge weights $W(S_i, S_j)$ between two nodes S_i and S_j are calculated using a similarity and dissimilarity measure, W^+ and W^-, respectively. We considered different inputs for our use-case (see Sec. 5) and image ResNet features similar to [16] were determined the best.

For the positive similarity weight W^+, the features from each sequence clustered into N_g *global* clusters via K-means. Thus, the frequency at which each two object sequences share the same clusters is indicative of how similar the objects are. The positive weight is the number of features vectors that appear in the same cluster scaled by a hyperparameter λ. The negative similarity weight W^- makes use of *local* intra-sequence K-means clustering, which serves the function of grouping each object's various viewpoints into N_l clusters. The computation of the weight between two sequences S_i and S_j is treated as a linear assignment problem - through a pair assignment matrix $X_{k,m}$ each cluster $C_{k,i}$ is assigned at most one cluster of the other sequence $C_{m,j}$ such that the distance between the assigned pairs is minimal. In our modified version of this weight, we normalise the negative weight by the number of pairs N_p and the number of dimensions N_d. See Eq. 3:

$$W^-(S_i, S_j) = \frac{\min_X \sum_k \sum_m X_{k,m} ||C_{k,i} - C_{m,j}||_2}{N_p . N_d} \quad \text{s.t. Each cluster being assigned to at most 1 pair} \tag{3}$$

As in [16], the total similarity weight is strictly non-positive (see Eq. 4):

$$W(S_i, S_j) = \max\left(\lambda W^+(S_i, S_j) - W^-(S_i, S_j), 0\right) \tag{4}$$

The graph is used to sample positive or negative pairings by random walks with transition probabilities based on the similarity edge weights. The min-max normalised negative similarity $W^{-\prime}$ is used as our confidence c in how negative the pairings are (or subtracted from 1 for positive pairs) instead of the complicated function defined in [16].

4.3.3 Hard Classification

As in [16], for *DON+Hard* the triplets (anchor A, positive P, and negative N) of sample frames are generated using the similarity graph and fed into a projection network comprised of two fully connected layers with ReLU activations. The projection network is trained via triplet loss scaled by our confidence c and margin M. The loss is strictly non-negative by applying ReLU:

$$L = ReLU\left(||A - P||_2 - ||A - N||_2 + c.M\right) \tag{5}$$

The resulting projection output is a continuous latent class representation. Finally, the representations of the training data are grouped into K clusters, determining the discrete classes. In inference time, assuming the input belongs to one of the existing classes, it can be projected and matched to the closest cluster. We denote this as training phase one. In the second phase, the DON iteratively accepts two kinds of image pairs as inputs with equal probability: (i) same sequence pairs that consist of two different frames of the same object from the same sequence and (ii) different sequence pairs that consist of two frames from random different sequences. In the different sequence scenario, the objects' discrete classes are inferred by assigning them to one of the K clusters - if their classes are the same, the pair is ignored, otherwise - non-match pixel pairs are generated and used for DON loss. In the same sequence, both match and non-match pairs are generated.

4.3.4 Soft Classification

For the DON+Soft variant, the similarity graph is generated with all available sequences (training phase one). A random sequence is sampled and a negative sequence pairing is randomly chosen based on the transition probabilities of the similarity graph. Two frame samples are taken from the initial sequence (anchor A and positive P) and one from the negative sequence, N, forming a triplet. The triplet is passed through the DON. Only non-matches are generated for the negative pair. A combination of the DON pixelwise match and non-match losses is used. The negative pair does not have any matches, instead its $L_{non-match}$ is scaled by the confidence c in the negative pairing, thus if there is strong belief that the pair is from the same class, the loss is smaller. The total loss is defined as follows:

$$L = L_{pos,non-match} + L_{pos,match} + c.L_{neg,non-match} \tag{6}$$

4.4 Hyperparameters

Unless otherwise specified, all trainings are done for $3,500$ iterations, which is sufficient as we observed convergence at $1,000$. The learning rate is set to 10^{-4}, with a decay of 0.9. DON margin parameter is set to 0.5. For the similarity graph, we used $N_l = 5$ and $N_g = 300$ clusters, and $\lambda = 0.1$. For *DON+Hard*, the classification network is trained for 500 steps before training the DON model.

5 Experiments

With our experiments we want to answer how effective our method is at separating object descriptors based on object categories. We investigate both qualitatively and qualitatively in this section.

5.1 Similarity

For our method to work, we need to effectively disentangle object representations. In this section we test the ability of the full classification model (i.e. consisting of Similarity Graph and Projection Network as in *DON+Hard*) to work with DON-compatible object sequences. We consider three input types: (i) Raw RGB; (ii) output of pre-trained frozen ResNet50; (iii) Masked Descriptor Image produced by a DON trained on match pairs for 500 steps. All inputs have been cropped to fit only the object via the object mask's bounding box, and interpolated to a fixed size.

Data	Raw Image	ResNet Features	Masked Descriptor
Simulated @$K = 2$	52.93%	**99.20%**	96.31%
Simulated @$K = 8$	22.13%	**95.25%**	76.23%
Real @$K = 2$	51.00%	**97.80%**	85.26%
Real @$K = 8$	16.07%	**93.12%**	71.09%

Table 1: Comparison of classification accuracy for different input types.

We test both on simulated (cans vs shoes) and real objects (hats vs shoes), where each object category contains 4 separate instance classes. We take 600 random images for training of the model and then test its cluster assignment on $2,000$ random test images of known object instances from unseen sequences. Inference into clusters is done via K-Means with $K = 2$ and $K = 8$ clusters corresponding

to the number of object categories and instance classes respectively. Note that K does not affect training. Cluster assignment to ground truth classes is done via a minimum linear sum in bipartite graphs [18]. The model accuracy is determined as the fraction of images that are correctly assigned. As can be seen in Table 1, the ResNet features appear far superior over other inputs. Not only are they effective in separating the features into categories but also into object instance classes.

5.2 Descriptors Evaluation

How effective is the separation? We first aim to show whether the descriptors produced by our methods are effective in separating the classes and how they compare to DONs trained with ground truth labels and without any labels. The models are trained on simulated training data containing 8 instance classes from 2 categories. The descriptors of 50 random images are produced and 400 random on-object pixels are sampled from each. These pixels are then passed through a TSNE projection resulting in Fig. 4. Even without any parameter informing the *DON+Hard* model that there are two object categories, we observe a clear separation of two clusters containing only objects from that category. Our qualitative evaluation demonstrates that the method is effective in separating objects, having similar objects share similar descriptor spaces. Comparing it with the *DON+Soft*, there is no clear discrete separation between the classes, but there's a gradual transition between them. We want to note that this is closer to how we interpret objects ourselves - if two objects have some similar features such as a colour, a handle, or other, we notice that similarity, while still detecting the overall difference between the objects.

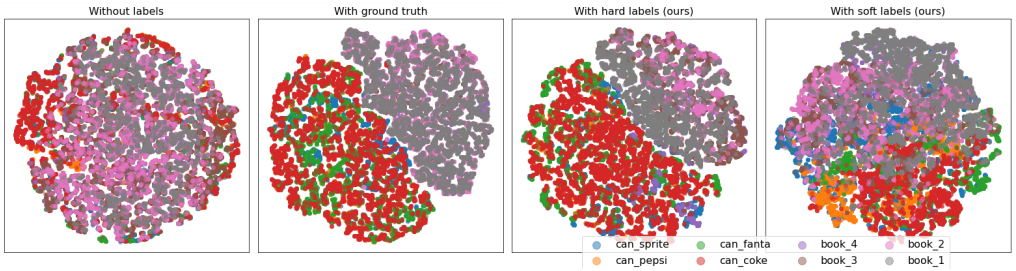

Figure 4: TSNE projection of randomly picked pixels from descriptor images produced by DONs trained without classification, with discrete ground truth labels, and our *DON+Hard* and *DON+Soft* methods. Eight classes are used from two categories (books and cans). Note that in *DON+Hard* two naturally emerging halves are observed, separating the two categories, despite using $K = 5$ class clusters during training to showcase the difficulty of not knowing the exact number of classes.

How does the quality of correspondences change? Given the descriptor at a random point from a query image, its best match in a target descriptor image is found as the one with minimal $L2$-norm. When working in single object scenarios, the original DON finds good semantic correspondences between semantically corresponding objects. However, as soon as there are multiple objects in the target image, the quality of the matches falls. To test this, we create new images, with unseen object instances in visually cluttered scenes, either through image collages or real photos (see examples in Fig. 5). We manually label a selection of points on a set of 40 training images and the set of 20 test

Figure 5: Examples of multi-object test images in cluttered scenes: shoe (left), hat (middle), and both (right). Note that some test images contain multiple training objects, e.g. a hat and two shoes.

images, each having labelled semantically significant locations (when not occluded). For example, this includes semantically distinctive points such as tip, top and back of a hat. This results in a

total of 432 pixel pairs for multi-object matches and 1218 for single-object matches. The closest descriptors of the labelled points in the training images are found in query images from the test set. The distance between the best match and the labelled point is the error. We plot the normalised error versus the fraction of images as a cumulative distribution in Fig. 6. The quality of our matches is shown in Fig. 7 for a query on an image containing novel instances of known instance classes.

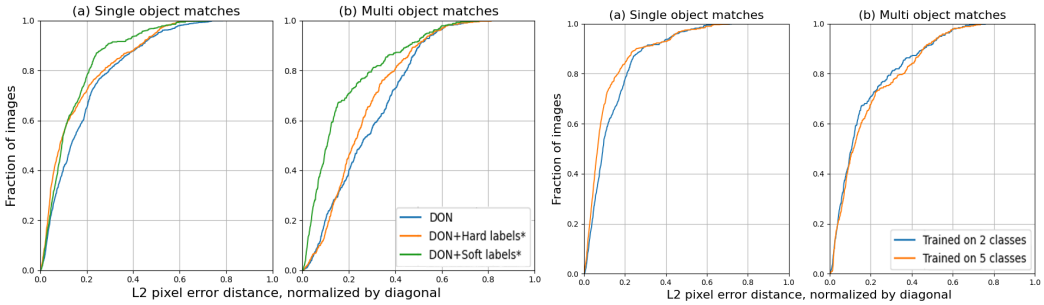

Figure 6: Cumulative Distribution Function (CDF) of L2 pixel error distance normalised by the image diagonal for single and multi-object queries. **Left:** comparing our methods (denoted with *) with DON. The soft labels (green) most effectively retain the good match correspondences in multi-object queries with undeterred performance for 67% of matches. **Right:** comparing *DON+Soft* performance when trained on shoes and hats only (blue) vs. trained with three extra classes.

As it can be seen both qualitatively and quantitatively, DON+Soft produces more robust correspondences in multi-object scenarios. Surprisingly there was the slight improvement in single-object matches. We believe this could be due to the contrast between objects encouraging the descriptors to be more specific and informative. We also trained *DON+Soft* on three extra classes of toys (extending it with 10 sequences), to determine how much of the information is retained with the addition of new observations. As seen in Fig. 6, the change in performance is minimal, while there is an even smaller error in single object matches.

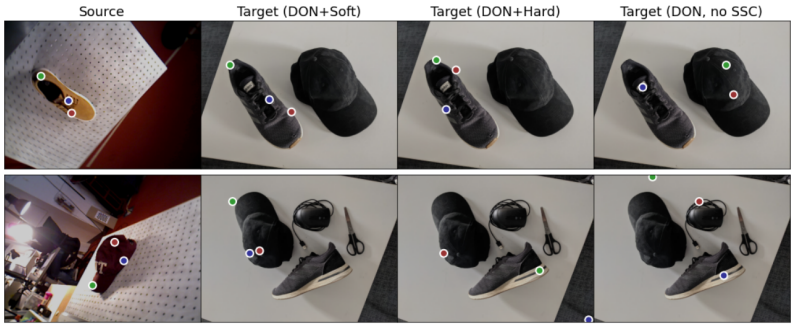

Figure 7: Random points from query images (left column) matched to the closest descriptor points in the target images with *DON+Soft*, *DON+Hard*, and no self-supervised classification (original). Each coloured dot represents a queried pixel and its best match in the target images. We show that the *DON+Soft* method produces better matches which reaffirm the quantitative results.

5.3 Real Experiment

In order to showcase the applicability of the model on a real robot we set up the following experiment. We use a Franka Emika Panda robot arm equipped with a RealSense D435i RGB-D camera. Firsly, a point is selected on an image of an object from the training set, in this case, a shoe or a hat. Then the robot finds the best match within its environment, by querying the trained DON+Soft on the camera RGB image. The correspondent pixel is projected into 3D space via the depth image and camera-to-world transformation. Finally, the robot produces a grasp for said point. Note that the objects used in the experiment are not part of the training set, and the camera used by the robot is different from the ones used for the data gathering. The clutter observed by the robot contains both known objects on which the model is trained and novel ones - to check that the model does

Figure 8: Grasping given a point: the model finds the best match to a selected point (shown in corner) within the robot's view, the pixel is projected into 3D space, the robot produces a grasps.

not confuse the correspondences with either. The source object, source point on object as well as the clutter configurations were varied to ensure robustness. See Fig. 8. The correspondences are correctly placed on the object that was queries during all 20 trials. The only correspondence failure occurred when the point found was at the edge of the queried object.

6 Conclusions

Limitations: Our method shows more robust matches than its predecessor in multi-object scenarios. One failure case we observed is how our method deals with occlusion. Matches to occluded points are found in completely wrong locations which indicates that although the descriptor subsets for similar object are similar, the individual distances between descriptors within the subsets are big. Querying for best-matches does not consider neighbouring descriptors, geometric consistency or other metrics which likely causes some of the other errors in our best-match correspondences. The DON in its current form is unable to work with dynamic training scenes. This could potentially be alleviated with the use of multiple viewpoints or tracking pixels with optical flow. Moreover, since the current system relies on masks of the input sequence objects, it could be extended to multi-object training scenes by adding a semantic segmentation network. The use of K-Means in *DON+Hard* leads to computational complexity scaling with number of sequences, as well as dealing with a constant number of clusters K when the real number of classes is unknown. In our exploratory work, to alleviate these issues we tried Mean Shift Clustering, Bayesian Gaussian Mixture Models and DBSCAN [19]. However, it was found that the classification accuracy on training data dropped significantly, likely because the latent classes are not described by normal distributions. *DON+Soft* would be unaffected by this since it purely relies on similarity measures.

Applications: This work enables applications that might treat different classes of objects differently. Here we provide three pick-and-place examples: (i) given some knowledge base of different objects and graspable points on them, the method can be used to automatically detect the closest match points even in cluttered multi-object scenes; (ii) or the opposite way, the model could see an object, infer its latent class and match it to the closest of its class clusters, thus generate the best grasping points for that class; (iii) alternatively, the model could be used to observe how people interact with objects, and learn which descriptor-points are suitable grasping points for each self-supervised class. In terms of more complex applications, we believe this representation could pave the way toward methods such as self-supervised robot affordance learning and action imitation.

Future Work: In this paper, we extended an existing method for self-supervised object descriptors to perform more accurately in multi-object queries and cluttered scenes. We showcase its improvement over its predecessor both qualitatively and quantitatively. Further analysis of the method could explore how having novel objects vs known objects in the background of a scene affects the performance, i.e. would it be better for the model to be trained on everything it sees, or does performance degrade once an object has been 'learned'. Future work will be focused on making the descriptors more useful by grounding them to actionable representations, and extending the training toward training in the wild from dynamic unstructured scenes.

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